Multienergy element-resolved cone beam CT (MEER-CBCT) realized on a conventional CBCT platform

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(Received 19 December 2017; revised 29 July 2018; accepted for publication 20 August 2018; published 22 September 2018)

Purpose: Cone beam CT (CBCT) has been widely used in radiation therapy. However, its main application is still to acquire anatomical information for patient positioning. This study proposes a multienergy element-resolved (MEER) CBCT framework that employs energy-resolved data acquisition on a conventional CBCT platform and then simultaneously reconstructs images of x-ray attenuation coefficients, electron density relative to water (rED), and elemental composition (EC) to support advanced applications.

Methods: The MEER-CBCT framework is realized on a Varian TrueBeam CBCT platform using a kVp-switching scanning scheme. A simultaneous image reconstruction and elemental decomposition model is formulated as an optimization problem. The objective function uses a least square term to enforce fidelity between x-ray attenuation coefficients and projection measurements. Spatial regularization is introduced via sparsity under a tight wavelet-frame transform. Consistency is imposed among rED, EC, and attenuation coefficients and inherently serves as a regularization term along the energy direction. The EC is further constrained by a sparse combination of ECs in a dictionary containing tissues commonly existing in humans. The optimization problem is solved by a novel alternating-direction minimization scheme. The MEER-CBCT framework was tested in a simulation study using an NCAT phantom and an experimental study using a Gammex phantom.

Results: MEER-CBCT framework was successfully realized on a clinical Varian TrueBeam onboard CBCT platform with three energy channels of 80, 100, and 120 kVp. In the simulation study, the attenuation coefficient image achieved a structural similarity index of 0.98, compared to 0.61 for the image reconstructed by the conventional conjugate gradient least square (CGLS) algorithm, primarily because of reduction in artifacts. In the experimental study, the attenuation image obtained a contrast-to-noise ratio ≥ 60 , much higher than that of CGLS results (~ 16) because of noise reduction. The median errors in rED and EC were 0.5% and 1.4% in the simulation study and 1.4% and 2.3% in the experimental study.

Conclusion: We proposed a novel MEER-CBCT framework realized on a clinical CBCT platform. Simulation and experimental studies demonstrated its capability to simultaneously reconstruct x-ray attenuation coefficient, rED, and EC images accurately. © 2018 American Association of Physicists in Medicine [<https://doi.org/10.1002/mp.13169>]

Key words: cone beam CT, dictionary, elemental-resolved reconstruction, iterative algorithm, kVp-switching, multi-energy

1. INTRODUCTION

Cone beam CT (CBCT) is the most widely used image guidance tool in radiation therapy.^{1,2} However, its current clinical

application is still limited mainly to acquiring anatomical information for patient positioning. It is highly desirable to explore the maximal potential of the CBCT platform to enable novel imaging capabilities and to support more

advanced applications in radiotherapy. One possible direction is to explore the energy dimension. In the diagnostic CT regime, the advantages and potential of incorporating the energy dimension have been clearly demonstrated over the years in a number of example problems. These include, but are not limited to enhancing visualization of a contrast agent^{3,4} and characterizing tissue properties to support treatment planning in photon^{5,6} and proton radiotherapy.^{7–11} With these successes, it is expected that employing the energy dimension would offer new capabilities in the CBCT regime as well.

In diagnostic CT, dual energy imaging capability can be achieved via different approaches, such as rapid kVp switching,¹² dual source scanning,¹³ and energy discriminating detection.^{14,15} Multienergy CT is also emerging via advanced photon-counting detection technology.^{16,17} Nonetheless, none of these approaches is available yet on a standard CBCT platform used in a radiotherapy clinic. This study's first contribution is to achieve multienergy imaging capability on a standard CBCT platform via kVp switching data acquisition and to demonstrate the feasibility of this approach. The second contribution of this study is a novel multienergy element-resolved (MEER) CBCT image reconstruction algorithm. In a CBCT scan, the number of projections is much lower than in a typical CT scan (~1000). Under a kVp switching scan, if the projections were further divided into different kVp channels, the low number of projections per kVp channel would inevitably lead to image artifacts, which would require advanced image reconstruction algorithms. This paper proposes a new method that simultaneously reconstructs CBCT images at all kVp channels as well as relative electron density to water (rED) and elemental composition (EC) of each voxel. In addition to using a spatial regularization in a tight wavelet frame form^{18–20} and a regularization along the energy direction inherently imposed by the consistency condition among x-ray attenuation, EC, and rED, the algorithm also uses a dictionary approach to incorporate prior knowledge regarding EC of common human tissues.

2. MATERIALS AND METHODS

Figure 1(a) depicts the overall structure of the proposed MEER-CBCT framework using an example case with three kVp channels. A standard CBCT platform used in radiotherapy is controlled to perform a kVp-switching scan. In one gantry rotation, the kVp levels at different projections are set to sequentially cycle through a few predefined kVp levels. Figure 1(b) shows that kVp depends on projection angle in an example with three kVp levels. The resulting projection data consist of 360 projections with an angular increment of 1°. Each energy level has a subset of 120 projections with an angular increment of 3°.

After the data acquisition step, a simultaneous image reconstruction and element decomposition algorithm are employed to concurrently reconstruct images of the x-ray

attenuation coefficient at different kVp levels, rED, and EC. Let $x = [x_1, x_2, \dots, x_N]$ denote a set of N vectors, and each x_i is a vector containing the image of the x-ray attenuation coefficient at the i -th kVp channel. Let ρ be the rED image, and $\lambda = \alpha\Omega$ gives the representation of EC over a dictionary Ω . The problem of simultaneous image reconstruction and decomposition is formulated in a nonconvex optimization form:

$$\begin{aligned} \{x, \rho, \alpha\} = \arg \min_{x, \rho, \alpha} & \frac{1}{2} \sum_{i=1}^N \|A_i x_i - y_i\|_2^2 \\ & + \eta \sum_{i=1}^N \|W x_i\|_1 \\ & + \frac{\beta}{2} \|x - \rho \cdot (\alpha\Omega K + K^c)\|_F^2, \\ \text{s.t. } & \|\alpha\|_0 < s, \alpha_j \geq 0, \sum_j (\alpha\Omega)_j = 1. \end{aligned} \quad (1)$$

Here, A_i and y_i are system matrix and projection data, respectively, of the i -th channel. W indicates a tight wavelet frame (TF) operator in the image domain.^{19,20} Penalizing the L-1 norm of the transformed image regularizes the image to help remove image noise while preserving the edges.

The third term in the objective function is introduced to ensure consistency among the reconstructed images x , rED ρ , and EC λ , where for each voxel, λ is a vector whose l -th element λ_l is the fraction of electron density of the l -th element with an atomic number Z_l . This study considers six elements (H, C, N, O, P, and Ca) that account for most human tissues. An empirical forward model^{21,22} $x_i = \rho(K_i^{PE}\tilde{Z}^{3.62} + K_i^R\tilde{Z}^{1.86} + K_i^C)$ is utilized with $\tilde{Z} = (\sum_l \lambda_l Z_l^{3.62})^{\frac{1}{3.62}}$ and $\hat{Z} = (\sum_l \lambda_l Z_l^{1.86})^{\frac{1}{1.86}}$. K_i^{PE} , K_i^R and K_i^C are constants characterizing contributions of the photoelectric effect, Rayleigh scattering, and Compton scattering, respectively, to the x-ray attenuation in the i -th kVp channel. These constants can be obtained via a calibration experiment. With some derivations,¹¹ it is easy to rewrite this forward model in the compact matrix form, $x = \rho(\lambda K + K_3)$. We also assume that λ has a sparse representation over a dictionary Ω , namely $\lambda = \alpha\Omega$, $\alpha_0 < s$, $\alpha_j \geq 0$, where s is a parameter that governs the sparsity level. In this study, the dictionary was constructed using ECs of 71 tissues from a reference human listed in Schneider et al.²³ The validity of this sparsity assumption comes from the completeness of the tissue dictionary. With a comprehensive dictionary, it is expected that EC of an unknown tissue can be expressed as a linear combination of only a small fraction of the total tissues listed in the dictionary. Finally, the condition $\sum_j \lambda_j = \sum_j (\alpha\Omega)_j = 1$ is imposed, because fractions of all chemical elements should add up to unity.

To solve this optimization problem, the alternating direction method of multipliers (ADMM)^{24,25} is employed. The main idea is to introduce auxiliary variables to decouple the original optimization problem, which allows it to be solved by iteratively performing the following five substeps. v and Z are auxiliary variables introduced by the ADMM, and u , Γ_1 , and Γ_2 are Lagrangian multipliers. t is the index of the iteration.

FIG. 1. (a) Structure of the proposed MEER-CBCT framework. Top: A kVp switching data acquisition scheme with three kVps as an example. Bottom: A reconstruction algorithm that simultaneously reconstructs x-ray attenuation coefficients at all kVps, EC, and rED incorporating prior EC information in a dictionary. (b) kVp level as a function of projection angle. (c) Spectra of three kVp levels at 80, 100, and 120 kVp used in the simulation study. [Color figure can be viewed at wileyonlinelibrary.com

$$x^{(t)} = \arg \min_x \frac{1}{2} \|x - \rho^{(t-1)}(\alpha^{(t-1)}\Omega K + K_3)\|_F^2 + \frac{\beta}{2} \sum_i \|A_i x_i - y_i\|_2^2 + \frac{\gamma_1}{2} \|Wx\|_1 + \|u^{(t-1)} - v^{(t-1)}\|_F^2, \quad (2)$$

$$v^{(t)} = \arg \min_v \frac{\gamma_1}{2} \|v - Wx^{(t)} - u^{(t-1)}\|_F^2 + \eta \|v\|_1, \quad (3)$$

$$u^{(t)} = u^{(t-1)} + Wx^{(t)} - v^{(t)}, \quad (4)$$

$$\alpha^{(t)} = \arg \min_\alpha \frac{1}{2} \|\rho^{(t)}(\alpha\Omega K + K_3) - x^{(t)}\|_F^2 + \frac{\gamma_2}{2} \|\alpha \mathbf{1}_M - \mathbf{1}\|_2^2 + \delta_+(\alpha), s.t. \|\alpha\|_0 \leq s \quad (5)$$

$$\rho^{(t)} = \arg \min_\rho \frac{1}{2} \|\rho(\alpha^{(t-1)}\Omega K + K_3) - x^{(t)}\|_F^2, \quad (6)$$

Due to space limitations, the algorithm is summarized in Table I. Interested readers can refer to the literature for more details.^{24,25} The subproblem with respect to α requires an inner iteration because of its complexity.

To test the proposed algorithm, a proof-of-principle simulation study was performed with a numerical NCAT phantom.²⁶ The NCAT phantom was segmented into lung, muscle, and bone regions, and each region was assigned the reference human's tissue properties (EC and rED).²⁷ A kVp-

switching scan with three channels of 80, 100, and 120 kVp and their spectra are displayed in Fig. 1(c). In a full 360 gantry rotation, 360 equiangular spaced x-ray projections were computed as $y = \int DE\phi(E)e^{-\int \mu(E,x)dl}$, where y is the projection data, $\phi(E)$ is the energy spectrum depending on the projection, and the integral in the exponent is evaluated using Siddon's ray-tracing algorithm. $\mu(x)$ is the linear attenuation coefficient calculated based on materials at each pixel. Poisson noise was then added following a realistic distribution.²⁸

Then, the images were reconstructed using the proposed algorithm, a conventional conjugate gradient least square (CGLS) method,²⁹ and an iterative method with a TF regularization.^{18,19} The CGLS method reconstructs images at each kVp channel independently by solving a least square problem, $x_i = \arg \min_{x_i \geq 0} \|A_i x_i - y_i\|_2^2$, with the conjugate gradient method. The TF method regularizes the least square problem with a sparsity term, that is, $x_i = \arg \min_{x_i} \|A_i x_i - y_i\|_2^2 + \eta \|Wx_i\|_1$. The reconstructed images of x-ray attenuation, EC, and rED were quantitatively evaluated by comparing with corresponding ground-truth values. In addition, since our algorithm has a uniform structure that is applicable to cases with different numbers of kVp channels, we compared results under different numbers of channels by performing a simulation study using two energy channels of 80 and 120 kVp.

The feasibility of MEER-CBCT on a standard CBCT platform was further demonstrated in an experimental

TABLE I. Reconstruction–decomposition algorithm of MEER-CBCT.

Input: $\alpha^{(0)}, \rho^{(0)}, v^{(0)}, u^{(0)}, z^{(0)}, \Gamma_1^{(0)}, \Gamma_2^{(0)}, \beta, \gamma_1, \gamma_2, \gamma_3, \eta, s$ and a stopping criterion ϵ ;

Output: x_{opt}, α_{opt} and ρ_{opt}

Procedure:

1. Set main loop index $t = 1$;
2. Subproblem in Eq. (2): Compute $x^{(t)} = (I + \sum_i A_i^T A + W^T W)^{-1} (\rho^{(t-1)} (\alpha^{(t-1)} \Omega K + K_3) + \beta \sum_i A_i^T y_i + \gamma_1 W^T (v^{(t-1)} - u^{(t-1)}))$,
which can be solved by a conjugate gradient least square (CGLS) method;

3. Subproblem in Eq. (3): Compute $v^{(t)} = \text{shrink}(Wx^{(t)} + u^{(t-1)}, \frac{\eta}{\gamma_1})$,

where $\text{shrink}(\cdot)$ is a soft-threshold operator;

4. Subproblem in Eq. (4): Compute $u^{(t)}$ according to Eq. (4);
5. Subproblem in Eq. (5):

Set inner loop index $p = 1$;

- (a) Compute $\alpha^{(p)}$ according to the following equations:

$$F^{(p)} = (\rho^{(t-1)})^2 (\Omega K + K_3)(\Omega K + K_3)^T + \gamma_2 \mathbf{1}_M \mathbf{1}_M^T + \gamma_3 I_N,$$

$$G^{(p)} = \rho^{(t-1)} x^{(t)} (\Omega K + K_3)^T + \gamma_2 \mathbf{1}_M^T - \Gamma_1^{(p-1)} \mathbf{1}_M^T + \gamma_3 z^{(p-1)} - \Gamma_2^{(p-1)},$$

$$\alpha^{(p)} = G^{(p)} (F^{(p)})^{-1};$$

- (b) Compute $z^{(p)}$ according to the following equation:

$$z_i^{(p)} = \begin{cases} \left(\alpha^{(p)} + \frac{\Gamma_2^{(p-1)}}{\gamma_3} \right)_i, & \text{if } i \in S_{\max}, \\ 0, & \text{otherwise,} \end{cases}$$

- (c) Compute $\Gamma_1^{(p)}, \Gamma_2^{(p)}$ according to the following equation:

$$\Gamma_1^{(p)} = \Gamma_1^{(p-1)} + \gamma_2 (\alpha^{(p)} \mathbf{1}_M - 1),$$

$$\Gamma_2^{(p)} = \Gamma_2^{(p-1)} + \gamma_3 (\alpha^{(p)} - z^{(p)});$$

- (d) If $\frac{\|\alpha^{(p)} - \alpha^{(p-1)}\|_F}{\|\alpha^{(p)}\|_F} < \epsilon$, set $\alpha^{(t)} = \alpha^{(p)}, z^{(0)} = z^{(p)}, \Gamma_1^{(0)} = \Gamma_1^{(p)}, \Gamma_2^{(0)} = \Gamma_2^{(p)}$; otherwise, set $p = p + 1$ and go to Step a);

6. Subproblem in Eq. (6): Compute $\rho^{(t)} = \frac{\sum_i x_i^{(t)} (\alpha^{(t)} \Omega K + K_3)_i}{\sum_i (\alpha^{(t)} \Omega K + K_3)_i^2}$;

7. If $\frac{\|x^{(t)} - x^{(t-1)}\|_F}{\|x^{(t)}\|_F} < \epsilon, \frac{\|\alpha^{(t)} - \alpha^{(t-1)}\|_F}{\|\alpha^{(t)}\|_F} < \epsilon$ and $\frac{\|\rho^{(t)} - \rho^{(t-1)}\|_F}{\|\rho^{(t)}\|_F} < \epsilon$, set $x_{opt} = x^{(t)}, \alpha_{opt} = \alpha^{(t)}$ and $\rho_{opt} = \rho^{(t)}$; otherwise, set $t = t + 1$, go to Step 2.

study conducted on a clinical Varian TrueBeam onboard CBCT platform (Varian Medical System, Palo Alto, CA) with a Gammex RMI 467 phantom (Gammex, Middleton, WI). The CBCT is operated to implement the kVp-switching scanning protocol under its developer mode, which allows a user to specify data acquisition conditions with a customized “xml” file.^{30,31} As such, the kVp of each projection was defined as illustrated in Fig. 1(b). Two

millimeter of Al filtration was used in the experiments, and half-value layers were 3.30, 4.11, and 4.87 mm Al for the three kVps, respectively. Tube mAs were set to 1.4, 0.8, and 0.5. These mAs values were selected, so the estimated noise levels in projection data would be similar among different channels. As with the simulation study, 360 equiangular projections were acquired in a full rotation.

FIG. 2. Three rows show images of the NCAT phantom reconstructed by the CGLS algorithm, TF-based algorithm, and the proposed algorithm, respectively. Display window is $[-500, 500]$ HU. [Color figure can be viewed at wileyonlinelibrary.com]

In all the reconstruction studies, the initial condition was set as $\alpha^{(0)} = \frac{1}{71}$ and $\rho^{(0)} = 1.0$. All other variables were initialized with zero. Stopping criterion was $\varepsilon = 10^{-3}$. We empirically fixed $\gamma_1 = 20$ and $s = 5$ as constants, as we found that these parameters lead to satisfactory results in all the tested cases. γ_2 , γ_3 , and η were manually tuned for satisfactory results. For both the CGLS and the TF algorithms, the stopping criterion is that the relative difference between images in two successive steps is less than $\varepsilon = 10^{-3}$.

3. RESULTS

Figure 2 presents the reconstructed images in the simulation study with three channels. The x-ray attenuation images reconstructed by the CGLS method contain severe noise and streak artifacts due to the noisy undersampled projection data. The TF method reduces most of the noise, though some streak artifacts remain. In contrast, artifacts in the images generated by the proposed method are profoundly suppressed, and structural edges are preserved. Quantitatively, our method is most consistent with the ground-truth, as indicated by the highest structural similarity index (SSIM).³² Table II provides detailed comparisons of SSIM and the three components in this metric. These quantities are computed using the code provided in Wang et al.³² by first calculating them for each patch and then averaging over the whole image. Among the three components of SSIM, the most significant advantage of the proposed method and TF method over CGLS is luminance, because at each patch, the presence of noise and streak artifacts in CGLS results

TABLE II. Luminance, contrast, and structure components of SSIM for reconstruction in simulation study.

kVp	Quantities	CGLS	TF	MEER
80	Luminance	0.7507	0.9986	0.9988
	Contrast	8.1321	8.4236	8.4718
	Structure	0.7538	0.7621	0.7669
	SSIM	0.6106	0.9631	0.9901
100	Luminance	0.7491	0.9986	0.9995
	Contrast	8.2466	8.5286	8.5599
	Structure	0.7515	0.7606	0.7645
	SSIM	0.6097	0.9696	0.9897
120	Luminance	0.7466	0.9978	0.9981
	Contrast	8.3783	8.6364	8.6963
	Structure	0.7491	0.7591	0.7618
	SSIM	0.6091	0.9736	0.9893

strongly affects image intensity. Figure 3(a) illustrates the convergence of the iterative reconstruction–decomposition process, though, note here that a theoretical justification of the convergence is not available for this complex optimization problem. To illustrate elemental decomposition accuracy, Fig. 3(b) shows the errors of Hydrogen (H), Oxygen (O), and Calcium (Ca) fractions and rED. Median errors of these quantities are 0.3%, 1.8%, 2.1%, and 0.5%, respectively. Figures 3(c)–3(f) presents images of the reconstructed ECs and rED. Comparing the results using three channels, the results using only two channels (80 and 120 kVp) have a slightly lower, but acceptable SSIM of 0.946 (images not

FIG. 3. (a) Convergence curve of the proposed algorithm; (b) Error plots of EC and rED: median error (red lines), 25th and 75th percentile (blue boxes) and error range. (c–f) Reconstructed images of H, O, and Ca fractions and rED. Display windows are [5%, 15%], [0, 75%], [20%, 30%], and [0, 1.90], respectively. (g) Error plots of EC and rED when using two energy channels: median error (red lines), 25th and 75th percentile (blue boxes), and error range. [Color figure can be viewed at wileyonlinelibrary.com]

shown due to space limitation). However, the insufficient spectral information yields relatively large errors in ECs and rED. Median errors of H, O, and Ca fractions and rED are 4.1%, 3.7%, 0.6%, and 11%, respectively, as shown in Fig. 3(g). Based on this observation, we will focus on the results obtained using all three energy channels in the experimental study.

Figure 4 presents the reconstructed images in the experimental study. The phantom contains nine tissue surrogates. Compared with the images reconstructed with the CGLS algorithm and the TF-based algorithm, noise and streak artifacts in the images reconstructed by the proposed algorithm are effectively suppressed. Mean contrast-to-noise ratios (CNRs) obtained by the proposed method are ≥ 60 , which are about four times higher and 1.5 times higher than those reconstructed by the CGLS and TF-based methods, respectively. The improvement in CNR is mainly because of reduction in noise. Regarding EC, Fig. 5 shows that the median decomposition errors of H, O, and Ca fractions and rED are 3.0%, 2.4%, 1.3%, and 1.4%, respectively.

4. CONCLUSION AND DISCUSSIONS

This letter proposes a novel MEER-CBCT framework that employs a standard CBCT platform available in a typical clinic to perform kVp switching data acquisition. Together with a novel algorithm that simultaneously reconstructs x-ray attenuation images at different kVp channels and EC and rED of each voxel, high quality multienergy and element-resolved images can be obtained. Simulation studies have demonstrated the accuracy and convergence of the reconstruction algorithm. Experimental studies performed on a Varian OBI system have shown the potential feasibility of the proposed framework as well as an end-to-end test with a median element decomposition error of 2.3% and rED error of 1.4%.

The ability to achieve satisfactory material decomposition results even with significantly overlapped energy spectra can be ascribed to accurate forward CT number model and regularization. First, minimizing the third term in Eq. (1) is effectively solving for λ from $x/\rho = \lambda K + K_3$. The matrix K characterizes contributions of each element to CT numbers of different kVp channels due to the photoelectric effect and

FIG. 4. Three rows show images of a Gammex RMI 467 phantom reconstructed by the CGLS method, TF-based method, and the proposed algorithm, respectively. Cylindrical inserts are: 1. cortical bone, 2. CB2–30%, 3. B-200, 4. inner bone, 5. solid water, 6. brain, 7. adipose, 8. LN300, 9. water. Display windows of the reconstruction images and the zoom-in patches are $[-500, 500]$ HU and $[-200, 200]$ HU, respectively. [Color figure can be viewed at wileyonlinelibrary.com]

Rayleigh scattering, whereas K_3 is the contribution of Compton scattering per unit electron density. A large spectrum overlap results in very similar vector entries in K_3 , but the matrix K still has acceptable numerical properties. The forward CT model accurately captures the dependence of photoelectric and Rayleigh scattering effects on material composition, making the determination of λ manageable. Second, although solving λ from the equation above is still underdetermined, the dictionary approach helps to regularize the solution by incorporating prior knowledge on human tissue EC. To further clarify this point, we conducted a test study in an extreme case using the same setup as in the simulation study but with only one spectrum (120 kVp). Our method failed in this case, and median errors were 8.7%, 15.0%, 23.7%, and 33.1% in H, O, and Ca fractions and rED, respectively. This observation, together with the results using two and three channels (Fig. 3), demonstrates the effectiveness of using multiple kVp channels despite substantially overlapped spectra.

The new capability to directly resolve elemental compositions through a kVp scan data acquisition is expected to add new potential to the widely available CBCT platform. For instance, this framework may potentially be used to facilitate online adaptive proton therapy. In proton therapy, estimating precise stopping power ratio (SPR) is a crucial task, which is known to be sensitive to the accuracy of rED and EC.

Recently, the potential of multienergy CT to improve SPR calculation has been clearly demonstrated.^{9,33–35} The proposed MEER-CBCT holds the potential to directly reconstruct EC and rED, based on which proton SPR can be calculated. This offers a method to map out an SPR image of the patient using the CBCT platform, potentially enabling accurate proton dose calculation and treatment replanning. The proposed method could also play a role in enhancing visualization of image contrast agents. With the known agent material included in the dictionary dataset, it may be possible to use the dictionary-based reconstruction method to directly obtain the distribution of the contrast agent. This capability may be applied to radiotherapy image guidance under a certain image contrast agent. For example, liver tumors are typically visualized with an iodine contrast agent in CT. Yet, it is difficult to achieve contrast-enhanced CBCT for liver tumor image guidance because of poor CBCT image quality.³⁶ Current patient positioning under CBCT yields substantial uncertainty. The proposed method may enable accurate liver tumor positioning under the iodine contrast. If iodine contrast is to be used repeatedly throughout a radiotherapy course, it is critical that the method be effective at a low concentration of the contrast agent.

The current study serves only as an initial attempt to demonstrate the proposed idea and to test its feasibility. It

FIG. 5. (a) Decomposition images of H, O, and Ca fractions and rED, respectively. Display windows are [0, 20%], [0, 83%], [0, 32%], and [0, 1.90], respectively. (a1) is displayed in a window of [17%, 20%], and (a2) is displayed in a window of [81%, 83%] to better visualize low-contrast inserts. (b–e) are errors of H, O, and Ca fractions and rED for each tested material: median error (red lines), 25th and 75th percentile (blue boxes), and error range. [Color figure can be viewed at wileyonlinelibrary.com

contains several limitations. First, both the simulation and the experimental studies may not adequately consider many practical issues. The simulation study ignores factors such as x-ray scatter. The experimental study uses a small phantom, for which the impacts of x-ray scatter and beam

hardening are expected to be small. The results in these studies only serve as a proof-of-principle. The proposed method will be further tested in more clinically relevant situations. When scattering and beam hardening effects are significant, it might be difficult for the proposed method to

obtain satisfactory results. To overcome these challenges, it may be necessary to incorporate projection data processing methods to ensure projection data quality.^{37,38} Second, the convergence of the proposed algorithm is only shown in a numerical study. A theoretical convergence analysis is absent. For this highly nonconvex problem, the iteration may not even converge in certain cases, although we have not observed this behavior. Third, the dictionary in this study contains only 71 materials for simplicity and computational efficiency. Theoretically, decomposition accuracy could be increased by using more materials in the dictionary, because this promotes sparsity. A recent related study¹¹ investigated the effect of dictionary size. Future research is needed to investigate the impact of dictionary size on MEER-CBCT.

One limitation of the MEER-CBCT method is patient motion during a kVp-switching scan. CBCT data acquisition is much slower than a diagnostic CT scan, so motion-induced data inconsistency becomes a concern. Correction approaches, such as a deformable image registration-based method^{39,40} or nonlocal mean-based methods,^{41,42} could be a solution for this problem. Our future studies will aim to overcome these limitations and improve the proposed method for clinical applications. Another limitation is computation time. It takes both CGLS- and TF-based algorithms ~90 sec to finish reconstruction, but ~30 min for the proposed method. While the long computation time impedes the practicality of MEER-CBCT, efficiency may be dramatically improved by using parallel programming techniques, for example, GPU, since most computational efforts in Table I are spent on matrix vector multiplication.

ACKNOWLEDGMENT

This study is supported in part by grants from National Institute of Health (1R21EB021545, 1R01CA214639, 1R01CA227289), Cancer Prevention and Research Institute of Texas (RP160661), National Natural Science Foundation of China (No. 81571771), and Ministry of Science and Technology of China (No. 2015BAI01B10). We thank Dr. Jonathan Feinberg for editing this manuscript.

DISCLOSURE

The authors have no conflicts to disclose.

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